Jurnal
Teknologi

Full Paper

PERFORMANCE PREDICTION OF WORKING MEMORY RETENTION USING EVENT-RELATED POTENTIAL SIGNAL TOWARDS CHILDREN

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Article history
Received
30 October 2015
Received in revised form
10 March 2016
Accepted
28 March 2016

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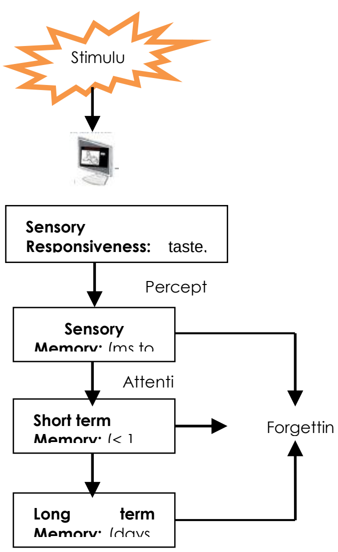
Graphical abstract



Abstract

This study is to investigate the Event-Related Potentials (ERP) from the background of Electroencephalograph (EEG) signal for working memory retention by using visual stimuli. The proposed analysis of ERP signal is to predict the performance of working memory retention for various frequency bands such as gamma, beta, alpha, theta and delta. This study is intended to process the EEG data into ERP data and analyze the ERP signal based on power spectrum density. This method is applied to data of normal children with age between 7 to 12 years old. Result showed that alpha power band increases during working memory retention towards visual stimuli compared to the other frequency band. 9 years old has the highest amplitude alpha power compared to the other group of age. Therefore, the alpha power band at the prefrontal cortex will be used for the next analysis of the working memory retention.

Keywords: Working memory, retention, EEG, ERP, Power spectrum

Abstrak

Kajian ini adalah untuk menyiasat isyarat *Event-Related Potentials* (ERP) daripada latar belakang isyarat Electroencephalograph (EEG) berdasarkan daya ingatan dengan menggunakan rangsangan pandangan. Analisis yang dicadangkan untuk isyarat ERP adalah untuk meramalkan prestasi daya ingatan pengekalan untuk beberapa jalur frekuensi seperti gamma, beta, alfa, theta dan delta. Kajian ini bertujuan untuk memproses data EEG kepada data ERP dan menganalis isyarat ERP berdasarkan ketumpatan spektrum kuasa. Kaedah ini digunakan untuk data daripada kanak-kanak normal yang berumur antara 7 hingga 12 tahun. Keputusan menunjukkan bahawa jalur kuasa alfa meningkat semasa daya ingatan pengekalan terhadan rangsangan visual berbanding jalur frekuensi yang lain. Kanak-kanak berumur 9 tahun menunjukkan mempunyai kuasa amplitud alpha yang paling tinggi berbanding kumpulan umur yang lain. Oleh itu, jalur kuasa alpha di korteks prefrontal dipilih untuk tujuan analisis seterusnya untuk pengekalan daya ingatan.

Kata kunci: Daya ingatan, pengekalan, EEG, ERP, kuasa spectrum

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1.0 INTRODUCTION

Over recent years, children have difficulty to remember things in a short of time. Working memory is to hold temporarily and manipulate information for cognitive tasks performed in daily life. Working memory also can hold only five to seven items at a time and have a small capacity to store the information [1]. Memory is the retention and ability to recall some information and involves awareness of the memory [2].

Figure 1 shows the block diagram of the working memory model. Human retention plays a key of role learning. In this model, there have 3 stages of retention such as sensory memory, short term working memory and long term memory. The learning process starts when the stimulus activates a sensory memory such as sound, taste, touch, vision and smell. Each sensory responsiveness has their own information and behavior. When the sensory memory received one of the input stimulus, the working memory only stays less than a millisecond for vision and 3 second for hearing [3]. After that, the information will replace with new information or input. Short term memory is retained for a short period of time. While, long term memory is the collection of memories that have been stored permanently over days, months and might be for years [4].

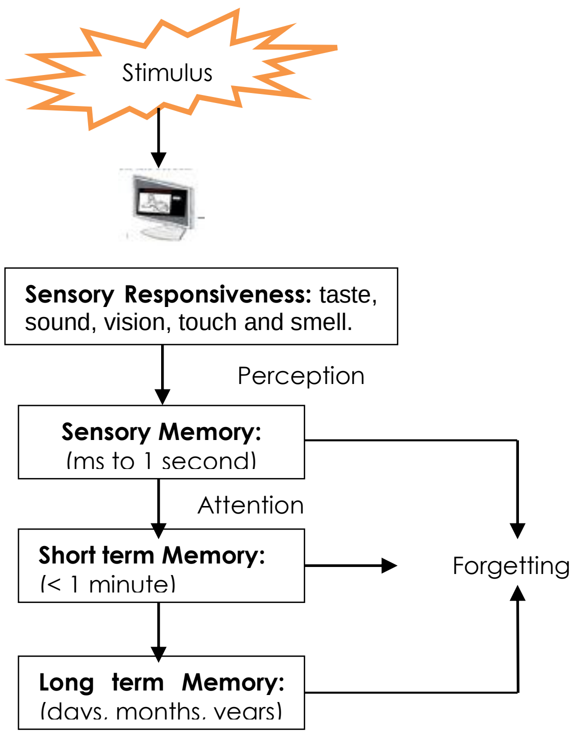

Figure 1 Block diagram of working memory model

Regarding on working memory retention towards children, this study focused on the sensory memory part only which is the information can receive for a short period of time. The information in working memory can be easily lost, thus to keep the information activated it has to be retained. The children will pay any attention to an external stimulus (visual) activities. In order to acquire sustained attention, sensory modulations of visual stimuli were given toward normal children to explore their working memory performance. Based on this stimulus response, Electroencephalograph (EEG) signal is recorded in order to analyze working memory retention.

EEG is medical equipment that reads brain activity by using scalp. As the EEG procedure is non-invasive, it is suitable to study the cognitive processes (perception, attention, memory and emotion). The EEG spectrum generated by EEG signal within five frequency bands, i.e., delta (< 4 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz), beta (13 to 30 Hz) and gamma (> 30 Hz) [5]. Event-related potentials (ERP) signal is used to present the stimulus combination that requiring some response stimuli.

One of the crucial issues to classify the relevant frequency bands~~,~~ is at which frequency bands the memory performances give more information. Some research has suggested that EEG frequency within the alpha band should be related to memory were induced the neural activity in the frontal cortex [6].

Thus, the power spectrum density is used to analyze which frequency band is the most suitable for working memory retention. Power spectrum density will indicate which frequency bands have the higher power level at the ERP signal. This analysis will be predicted by the theory of choosing the suitable frequency for working memory retention.

2.0 MATERIAL AND METHODS

2.1 Subjects

The participant of the study consisted of 97 normal children aged 7 to 12 years old which comprised of 57 boys and 40 girls. They had no previous history of neurological abnormalities.

2.2 Behavioral Assessments: Visual Stimuli and Procedure

First of all, in order to collect the EEG data, one subject was selected and the examiner presented the visual stimulation in front of the subject.

The visual stimulation that to be focused namely Phase 1 (The Study Phase) is illustrated in Figure 2. Phase 1 consisted of four pictures which are an animal pictures (elephant, tiger, cow, and monkey) in a black and white color. They were asked to focus their eyes on the computer monitor and follow the instructions given by the examiner. The stimulus program will ensure that the periods of the displays during the test are uniform for all subjects.

The task started with the white block on the screen as a fixation for 1 second, followed by the sequential presentation of four different animal pictures. Each picture was shown about 5 seconds and repeated two times. Each picture has a same grid position 4 x 4 block pictures with the width and height, 13cm (width) x 10cm (height) from the fixation screen. The screen will be automatically back into the fixation block (white color) after all pictures were presented.

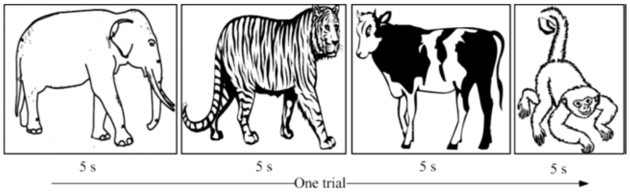

Figure 2 Phase 1: The Study Phase shows 4 different pictures

2.3 Research Design and Procedure

Figure 3 shows the summary of the entire flow process in this study. There are 3 stages to be completed which are data collection, signal processing and statistical analysis.

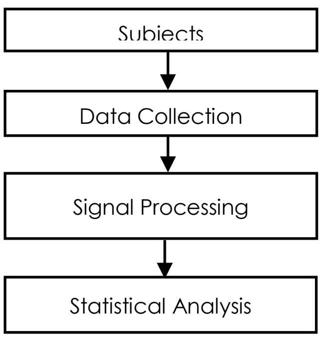

Figure 3 Workflow of the study

2.3.1 Data Collection

EEG data were recorded using Neurofax-EEG 9200 models and EEG recording can be achieved by placing electrodes on the scalp which attached to the subject's head. Figure 4 shows the experimental setup to collect the EEG signal recording. Each subject seated 25 cm from the monitor screen which display the visual stimulation. Scalp electrodes were places on their head according to the standard of 10-20 Electrode Placement and channels of F3, F4, Fz, F7 and F8 are chosen for working memory development. Then, the electrode board adapter was plugged into EEG data acquisition machine according to the standard color coded.

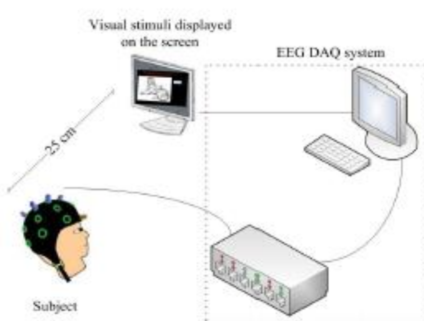

Figure 4 Experimental Setup

2.3.2 Electroencephalograph (EEG) Recording

The recorded raw EEG data were saved in ASCII code and converted into. Mat file format, in order to analyze the signal using MATLAB. Since EEG data were recorded continuously, the activity generated in response towards visual stimuli has the unwanted signal. The unwanted signal that is not related to the stimuli can be categorized as artifacts. After that, the study proceeds to remove noise inside the raw EEG signal using Independent Component Analysis (ICA) and wavelet de-noising.

Artifact Removal

ICA is used to remove biological artifacts such as eye movement, muscle movement and blinking. An important application of ICA is in blind source separation (BSS). BSS is the method to recover and estimate the independent source signals using the information of their mixtures observed at the recording channel [5].

Figure 5 shows the illustration of the BSS concept for mixing and blind separation of the EEG signals. A perfect separation of the signals requires taking into the structure of the mixing process. In this study, the BSS concept is applied to the 5 channels at the prefrontal cortex (F3, F4, Fz, F7 and F8). By using an equation (1), this process can separate the internal artifact.

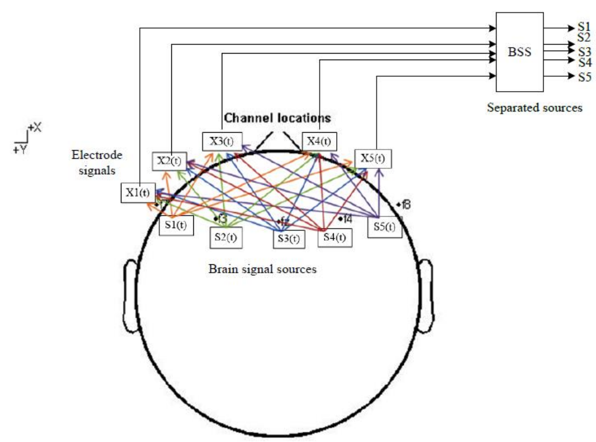

Figure 5 A schematic diagram of the Blind Source Separation (BSS) concept; mixing and blind separation of the EEG signals for 5 channel at the prefrontal cortex where $X_n(t)$ is the electrode signals, $S_n(t)$ is the brain signal sources, and Sn is the separated sources

Generally, all vector classified as a column vectors, the transpose of x, is a row vector. By using vector-matrix, the mixing model is written as in equation (2) that called BSS model or ICA model [7].

$$x_j = a_{j1}s_1 + a_{j2}s_s + \cdots + a_{jn}s_n \ \ for\ all\ j \qquad (1)$$

where vector a_1, ..., a_n is the columns of matrix which the scalp maps (pattern of potential), s is the sources activities, x is the vector of time varying electrode potentials. The independent components are latent variables that cannot be directly observed. Because of the mixing matrix is assumed to be unknown when estimating *a* and *s* matrices. Let denote x the random vector whose element are the mixtures $x_1,\ldots, x_n$ and s as the source activities that elements $s_1,\ldots,s_n$. Let A be the matrix after estimating the matrix a_{ij}, *W* as appear as inverse, and by given the EEG data, *X* will decompose it into source scalp maps multiplied by source activity, with *a* and *s* are unknown refer in equation (2) [8]:

$$s = Wx \tag{2}$$

The calculation of weights (*W*) signal from the original signal (*s*) is depending on the signal path from the electrodes that connected to the brain cell. Because of the recorded of cognitive memory more than one channel, the signals from all channels should be correlated and covariance. If the weights were known, the potentials in the sources (*s*) from an adequate number of channels signal can be figured [9].

While, wavelet de-noising is used to remove the external artifact such as power and line noise that occurs during the experiment. The underlying model for the noisy signal basically of the following equation (3) [10]:

$$s(n) = f(n) + \sigma e(n) \tag{3}$$

where *s* is the original signal of EEG signal at the level of *n*. *e(n)* is a Gaussian white *N* (0,1) and the noise level of *s* is theoretical to be equal to 1.

Segmentation and Averaging

Then, the clean EEG signal is segmented and averaged according to the visual stimuli to become ERP signals. Each segment from the background EEG signal is segmented from 100 to 600 ms and passed through a matched filter to give one feature that represents the maximum correlation between a segment and average ERP component. Within each segment, the signal measured statistically stationary, regularly with similar time and frequency statistics. As an example, an EEG recording for Phase 1 divided into 4 segments, according to the different visual stimulus. Each segment may have a different duration.

In the above statement, the ERP signal is originally divided into the background EEG and ERP before and after the stimulus time instant respectively. The ERP is divided into two segments, the early brain responses, which is a low-level high frequency signal and the late responses, which is high level of low frequency signal according to the equation (4)[5]:

$$x(n) = \begin{cases} x_1(n) & -L \le n < 0 \\ s_e(n-n_0) + x_2(n) & 0 \le n \le L_1 \\ s_1(n-n_0-L_1) + x_3(n) & L_1 \le n < N + L_1 \end{cases} \tag{4}$$

where $x_1(n)$, $x_2(n)$, and $x_3(n)$ are the background EEG before the stimulus, during the early brain response respectively. $s_e(n)$ and $s_1(n)$ are the early and late brain response to stimuli respectively.

The brain signals that corresponded to each stimulus were segmented into 5s, 10s, 15s, and 20s for Phase 1 to represent each location. Averaged and segmenting were applied to find the ERP signal so that a conclusive diagnosis on the working memory performance of a particular respondent could be made.

Event-Related Potential (ERP) Signal

ERP might occur due to allocation of attention to stimulus attended by memory. ERP is to represent stimulus evaluation time and amplitude. ERP also is a brain activity that occurs in response event that being internal or external to the subject [11]. The amplitude of ERP is usually smaller than the EEG signal which 10 µV than EEG (50 µV) [12].

The general advantage of ERP is the ERP can measure the non-stationary of neural activity and more relative to event stimuli [13]. Besides that, the capacity to the neural correlates of cognitive in real time which ERP can be measured in milliseconds [14].

Discrete Wavelet Transform Analysis

Discrete Wavelet Transform (DWT) is used to decompose the ERP signal into 5 different frequency bands (gamma, beta, alpha, delta and theta). Since the frequency sampling is 1000Hz, the ERP signal is decomposed into 8th level of decomposition.

DWT decomposition of signal can be written as in equation (5) [15]:

$$DWT_{t,k} = \frac{1}{\sqrt{2^j}} \int_{-x}^{x} x(t)\varphi\left(\frac{t-2^j k}{2^j}\right) dt \tag{5}$$

where DWT is the discrete wavelet transform, 2^j is the imaginary part to filter the signal, ψ is the mother wavelet, and x*(t)* is the original signal.

The signal is decomposed into high pass filter which is detailed coefficient (cD) and low pass filter which is approximation coefficients (cA) respectively. Decomposition of signal into cD and cA is expressed in equation (6) and equation (7) [15]:

$$d_1(k) = y_{high}(k) = \sum_n x(n) \times g(2k-n) \tag{6}$$

$$a_1(k) = y_{low}(k) = \sum_n x(n) \times h(2k-n) \tag{7}$$

where the detailed coefficient defined by the scalar product raw signal, *x(n)* with the scaling function, *g (2k–n)*. However, equation (7) is the approximation coefficient for down-sampling by a scalar product between raw signal *x(n)* and down-sampling *h(2k – n)*.

In accordance to the theory, level eight wavelet decomposition was selected since the frequency sampling used in this study was 1000 Hz. In this representation, the Approximation (cA) and Detailed (cD) coefficients (A1, D1, A2, D2, A3, D3, A4, D4, A5, D5, A6, D6, A7, D7, A8 and D8) were the frequency content from the original signal within the bands.

Power Spectrum Density

EEG signal comprised into various frequency bands such as gamma, beta, alpha, theta and delta. Those frequency band have different range of frequency and power spectrum.

Power spectrum density (PSD) describes the general frequency composition of the data in terms of the spectral density of its mean square value [15]. The mean square value of the frequency range is in equation (8) [16]:

$$\psi^2(f,\Delta f) = \lim_{T\to\infty}\frac{1}{T}\int_0^T x(t,f,\Delta f)^2 dt \tag{8}$$

The power spectrum density was organized according to the location of the brain. In order to determine the maximum value of the power spectrum, the dominant frequency is obtained. Based on the power spectrum, the highest value of the power spectrum from five frequency bands will use for the next analysis.

The aim of this analysis was to analyze which frequency band gave the highest power distribution toward working memory retentions. This analysis also can minimize the next further study and more focused at least one frequency band that gave more important for working memory retention. Figure 6 shows the flow of the pre-processing flow described.

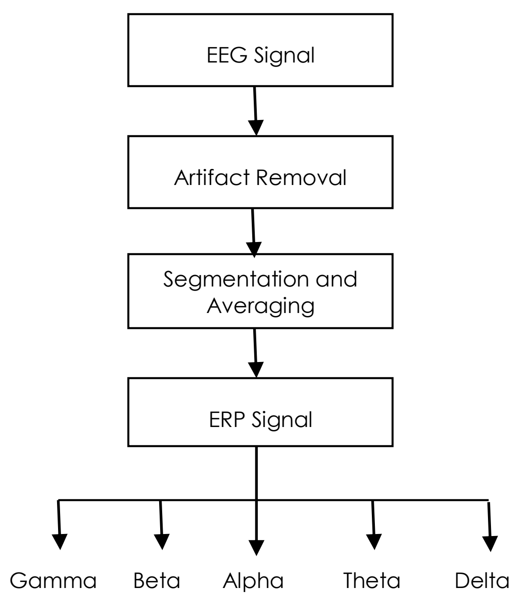

Figure 6 Block diagram of EEG signal processing system

2.3.3 Statistical Analysis

Figure 7 shows that the statistical analysis is performed to extract the feature parameter for each frequency band. The dynamic features are chosen like mean and standard deviation. Those features will act as an independent variable or as an input for the *t*-test analysis.

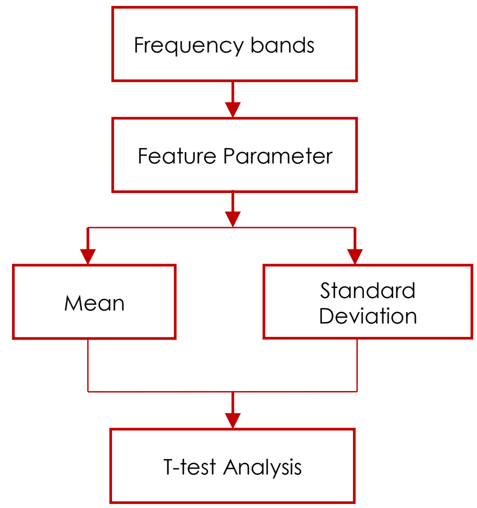

Figure 7 Block diagram of the statistical analysis system

Mean

Mean is the average of the summation of the observed values that are divided by the total number of observations. Equation (9) indicates the mathematical formula for finding the mean value.

$$\bar{X} = \frac{\sum_i X_i}{N} \tag{9}$$

where $\bar{X}$ is the mean value, X_i is the observed values and N is the total number of observations.

Standard Deviation

Standard deviation (σ) is the distance between one point to the mean value and measure of dispersion. Standard deviation is also one standardized value to show the distance of data from the mean. When the value of standard deviation is small, it is better because the estimation will be consistent. Based on the mathematical formula in equation (10) the value of standard deviation can be determined.

$$\sigma = \frac{\sum(X_i-\bar{X})^2}{N} \tag{10}$$

where $\bar{X}$ is the mean value of the sample data, X_i is the value for each point of the sample data. N is the total number of observations (sample), $(X_i - \bar{X})$ is the distance from mean to the data, $(X_i - \bar{X})^2$ is the zero value, which is the summation of the total of distance from the mean.

T-test Analysis

Before performing the classification analysis, the t-test analysis was done to predict whether all features are significant or not, according to the statistical threshold value (p < 0.001). If the features are significant, the classification can be made. *T*-test analysis is used to statistically analyze the similarities and differences between two normal distributions and categorize them based on the confidence interval of 95 %.

As aforementioned, the classifiers are predicting the variants that have a probability value between 1 and 0. If the subject has a probability of 0.5 and above, it is taken that the probability is 1 (i.e., the child has working memory retention) and vice versa. The hypothesis was assumed among a group of age (7, 8, 9, 10, 11 and 12 years old) to determine which group has more working memory retentions.

The next step is to determine whether the null hypothesis has been accepted or rejected with reference to the inputs of the independent variables - gender of respondent (Boy, Girl); age (7, 8, 9, 10, 11, and 12 years old); features. For the dependent variables, working memory retention (1 = having working memory retention, 0 = do not have working memory retention).

3.0 RESULTS AND DISCUSSION

3.1 EEG/ERP Signal Processing

Figure 8 shows the process from an EEG signal into ERP signal. First of all, raw EEG data was filtered using ICA and wavelet de-noising to remove unwanted noises.

After that, the EEG signal was segmented into event occurred and averaging the segmentation data in order to produce the ERP signal. The EEG signal was segmented into 4th segment according to the number of stimuli (elephant, tiger, cow and monkey). Figure 9 shows the segmentation of EEG to produce ERP signal for Phase 1.

Based on the ERP signal, DWT is used to decompose the ERP signal into 5 frequency bands which are gamma, beta, alpha, delta and theta. Figure 10 shows that the ERP signal of decomposition level by using DWT techniques. The ERP signals were decomposed into approximate coefficients (cA) and detailed coefficients (cD) by down-sampling by 2 until the original ERP signal find all the frequency range (D5; gamma, D6: beta, D7: alpha, D8; theta, and A8: delta).

Based on the ERP signal decomposition, the analysis will proceed with the power spectrum analysis, in order to determine the highest power among frequency bands.

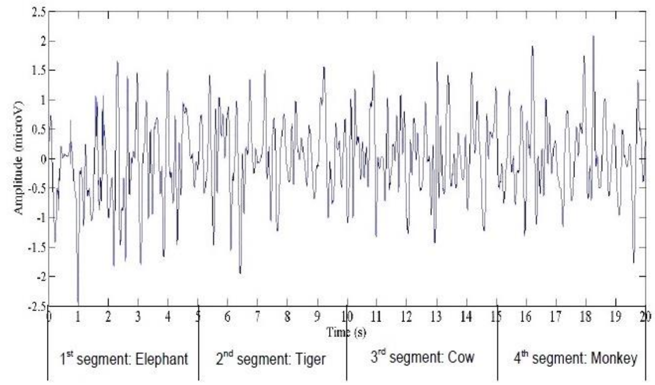

Figure 8 EEG signal segmented according to the stimuli for Phase 1 at the channel of Fz

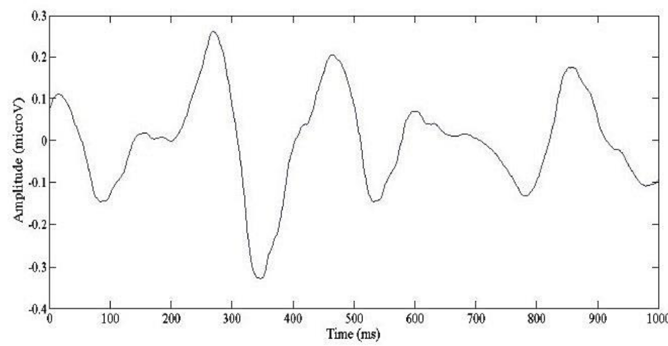

Figure 9 ERP signal: The waveforms created by averaging the segmented signals for Phase 1 at the channel of Fz

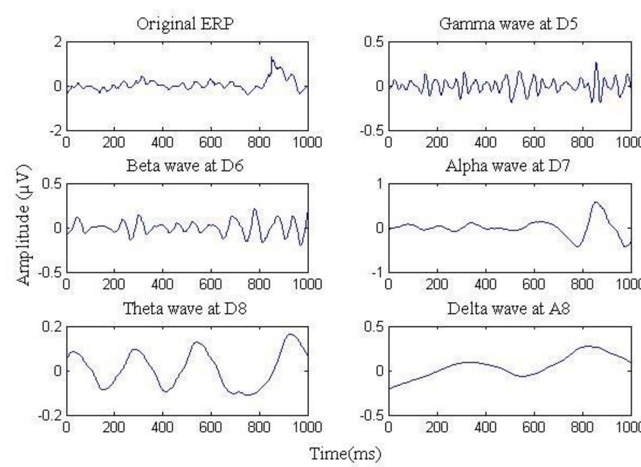

Figure 10 ERP signal decomposition using DWT to decompose the ERP signal into sub-band for different frequency bands at the channel of Fz

3.2 Power Spectrum and Frequency Analysis

Figure 11 shows the power spectrum density of the ERP signal at the prefrontal cortex from one of the subject. The power spectrum density of working memory retention is combined in one graph, in order to compare the different pattern of each frequency bands. The power spectrum density of working memory retention has evidently showed higher amplitude value at alpha band compared to other frequency bands.

The ERP signal showed a slight difference between each subjects and group of age. The comparison of frequency band values was obtained by determined the maximum power spectrum. Figure 12 shows the average of power spectrum density among a group of age. While working memory retention, the highest power will indicate the alpha band for all the groups. 9 years old children give the highest power of alpha which is 6.63 $\mu V^2/Hz$ compared to other groups. Mean while, 8 years old show the lowest power of alpha which is 5.19 $\mu V^2/Hz$.

In summary, the most noteworthy of ERP signal activity occurs at the alpha band. This alpha power is consistent with the previous study. Meaning that, alpha band gives higher power while doing visual stimuli for the working memory retention.

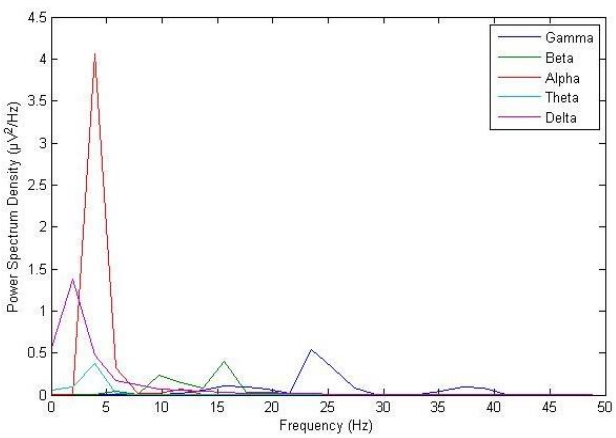

Figure 11 Average of power spectrum density obtained from 1 subject based on ERP recording

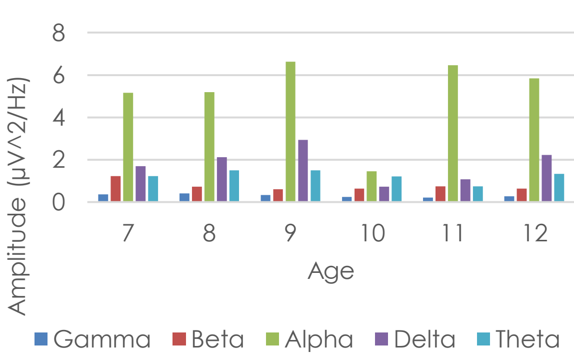

Figure 12 Bar chart of the average of power spectrum density among group of age population

3.2 *T*-test Analysis

The average of the power spectrum was then grouped into different bands for working memory retention. Mean and standard deviation of the power spectrum for working memory retention in various frequency bands. In order to support the analysis of the power spectrum which frequency bands will be significant with the visual stimulation task, the distribution of power spectrum is used. Besides that, the finding of power spectrum density were supported by statistical analysis which is *t*-test.

The *t*-test analysis is used to predict which frequency bands are significant or not, according to the statistical value ($p < 0.001$). The purpose using test statististically is to determine if the feature on a test is different for the two groups tested (i.e., have working memory retention or not). The mean *t*-test for each feature is applied to analyse if the t value falls into the critical region. If the t value falls into the critical region ($p < 0.001$), the null hypothesis is rejected. This approach is often used to test whether the feature lies on the normal distribution or not.

The statistical hypohesis as follow:

H_o: $\mu = \mu_o$
H_1: $\mu \neq \mu_o$

This prediction is used to predict that the sampled data come from a normal distribution. Table 1 shows that, all features are greater than 0.001. This implies that it is acceptable to assume the features of the frequency bands are normal and significantly different.

Table 1 Description statistics of *t*-test for Phase 1

Feature	*t*-test				
	Gamma	Beta	Alpha	Theta	Delta
Mean	0.1523	0.7213	0.0646	0.6965	0.9766
Std	0.3456	0.8851	0.0767	0.2074	0.0043

4.0 CONCLUSION

Analysis had been done to observe the pattern of power spectrum density for each frequency band. From the observation, alpha band have the higher power compared to the other frequency bands. Alpha band is the frequency band that proved whether the subjects in the working memory retention or not. By using power spectrum density, this study found that there is certain frequency band that discovered as the composition of the EEG signal when the subjects were exposed by visual stimulation.

It is obviously proved from the previous study the ERP power spectrum is high in frequency range at the alpha band which is 8 to 12 Hz during working memory retention. If the underlying mechanism of the alpha band is predicted, it can be applied on the clinical diagnosis for neurological disabilities [16].

On the other hand, alpha band will increase the speed of processing information and enhances cognitive performance [18] suggested that the alpha band in ERP signal are associated with attention processes [19-21]. From the statistical analysis, the value of p has been significantly different.

In conclusion, this study has been classified each frequency band for working memory using visual stimuli based on power spectrum density. The DWT is used to decompose the ERP signal with different frequency bands occurred. Power spectrum density is used to predict the performance of working memory retention for all frequency bands, in order to predict which is the most suitable for the next analysis. Thus, the proposed study method could be used for ERP classification to find out the suitable bands, to give an easier way for further analysis.

Acknowledgement

The author would like to thank all teachers and students at Sekolah Agama UTM for the permission for EEG data collection. Gratitude also goes to the Ministry of Science, Technology and Innovation Malaysia for the funding of this study under vote no. 4S094.

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